DEVELOPMENT OF PERSONALIZED DIET AND EXERCISE RECOMMENDER SYSTEM BASED ON CLINICAL DATA

PhD Synopsis submitted to CHRIST (Deemed to be University)
as partial requirement for the award of Degree of

DOCTOR OF PHILOSOPHY

IN

COMPUTER SCIENCE & ENGINEERING

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JANUARY 2020

ABSTRACT

The present health scenario indicates that thyroid diseases are a common challenge experienced by most individuals. According to the statistics in India, one out of eight women suffer from thyroid-related conditions such as hyperthyroidism, hypothyroidism, and thyroid cancer. It is imperative to maintain optimum levels of secretion of the thyroid hormones as the imbalance could lead to thyroid diseases. Therefore, thyroid patients must be vigilant regarding their iodine intake and follow a customized daily diet and exercise plan. The diet plan, along with balanced iodine levels must also be able to meet the patient's nutritional needs. A personalized diet plan could help thyroid patients to be more aware and focused on their body metabolism. Existing recommender systems usually provide diet recommendations in a generic manner and unfortunately, it may not be beneficial to patients suffering from a specific disease.

Content-based Neighborhood-Conditional RBM (CB-NCRBM) model has posited to recommend Top-3 diet and exercise plans for thyroid patients. The proposed model considers joint probability distribution of different scores using user profile. Similarly, preference and health scores are estimated based on the content features. These scores are fed as visible units to conditional RBM. The proposed model also integrates several content-based features such as user personal profile, thyroid disease information, food and exercise preferences. Information from the proposed recommender model is evaluated using recommendation error and classification accuracy metrics. The proposed hybrid model outperforms other collaborative filtering, content-based, and pure RBM models. The system also provides a feedback loop to enhance the quality of recommended diet and exercise plans, based on user experience.

Keywords: Food and Nutrition**,** Diet and Exercise Recommendations, Thyroid Disorders, Restricted Boltzmann Machines, Content-based Methods, Collaborative-based Filtering Approaches.

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1. INTRODUCTION

The key to pursuing a healthy lifestyle corresponds with practicing healthy habits. It is particularly important for the people suffering from some minor or major diseases to follow a healthy lifestyle. Digital health motivations and research investigations offer several recommendation systems to patients for the improvement of their health [1]. Majority of earlier studies depict that wrong and inadequate food intake may cause various health issues. The “World Health Organization” (WHO) estimates that around 30% of the world's total population is suffering from various diseases [2]. The Organization also reports that around 0.7 billion individuals suffer from iodine deficiency because of wrong and inadequate food intake [3]. Normally, people ignore the intake of nutritional food in the right quantity. A customized diet plan consists of the necessary nutritional elements like calcium, proteins, and vitamins that are needed to fulfil one’s nutritional requirements. It is essential for people to find the right diet plan for themselves- one that fulfils their nutritional needs and tastes.

Recommender systems improve the client’s experience by suggesting items of their choice. Facebook, Amazon, and Netflix use recommender models to attract people in order to promote their services and products. Recommender systems are broadly categorized into four popularly used approaches: (i) Collaborative filtering, (ii) Content-based, (iii) Knowledge-based, and (iv) Hybrid [4]. Collaborative filtering approaches use the past behaviors and choices of likeminded users to create recommendations. These methods compute nearest neighbor similarity measures using user’s behavior and ratings. Content-based strategies exploit a user’s profile to make recommendations; Knowledge-based methods derive inferences from user profiles and generate the recommendations; and Hybrid techniques combine two or more of the above-mentioned methods.

Most precise recommender systems generally use model-based techniques. RBM-Restricted Boltzmann Machines- is a model-based deep learning method [5]. RBM creates a low-dimensional feature-set of items with latent factors which captures the client's interests within different groups of food items. However, the interpretation of these features can be challenging. RBM has proved to be a promising tool to solve this issue as it learns and predicts the patterns in huge datasets to provide precise results [6].

It generates information about missing values and features by hiding the details of the data generation process [7].

The proposed model chooses the RBM method to produce recommendations of diet and exercise lists using food-item ratings. The current project extends the RBM model to neighborhood-Conditional RBM. The hybrid model integrates similarity, food preferences and health scores as extra visible units. The proposed model integrates content-based attributes which are extracted from the user's personal and medical profile, food and activity preferences, and meal types like Breakfast, Lunch, Snack and Dinner. The experimental results prove that the Content-based Neighborhood-Conditional RBM (CB-NCRBM) approach outperforms other collaborative filtering, content-based, and pure RBM models. The proposed model is validated using recommender error and classification accuracy measures.

1.1 Overview of Thyroid Disorder

The thyroid organ is a butterfly shaped endocrine gland. It is present at the lower middle portion of the neck. It controls the body's metabolism rate, temperature, and growth. There are three main thyroid hormones: TSH-Thyroid Stimulating Hormone, T3-Triiodothyronine and T4- Thyroxin [8]. The thyroid organ absorbs iodine nutrients from food and converts them into T4 and T3 hormones. A small sized pituitary gland present below the cerebrum, in the brain, secretes TSH. This gland controls the thyroid organ and indicates it to release T3 and T4 in required quantities. The hypothalamus controls the pituitary organ. In that, the hypothalamus identifies low thyroid hormone levels and releases thyrotropin hormone. This hormone activates the pituitary gland to release TSH, which controls the functioning of the thyroid organ in relation to the amount of secretion of thyroid hormones. Thyroid disorder prominently has two types, and these are differentiated by TSH and T4 and T3 values [9]. Hypothyroidism is underactive thyroid or low thyroid disorder, while hyperthyroidism is overactive thyroid disorder.

1.2 Impact of Diet and Exercise on Hypothyroidism

Dietary micronutrients are essential factors to generate the thyroid hormones. A balanced diet plays a crucial role in the prevention of thyroid diseases as it helps to regulate the generation of thyroid hormones. Iodine and other nutrients like selenium and zinc are needed to maintain the thyroid hormonal balance. Thyroid patients need to consume an appropriate amount of iodine. Insufficient or excess consumption of iodine and other nutrients may generate less or more thyroid hormones. Thyroid patients are recommended to consume a balanced diet which should contain the required amount of iodine [10]. The recommended diet for thyroid patients should also have restricted intake of goitrogenic food-items. In terms of exercise, Hypothyroidism is shown to reduce the patient's ability to exercise. However, regular exercise regimen can improve thyroid functions [11].

2. LITERATURE REVIEW AND RESEARCH CHALLENGES

The extensive research has been investigated in the field of healthcare recommendation systems. Various studies have designed and developed either physical workout-based or diet and nutrition-based recommendations systems. Very few studies are investigated with consideration of both diet and exercise recommendations together. Several research works have designed diet recommender systems for diabetic and cancer patients. The diet and physical exercise recommendation framework for thyroid patients is, however, under-researched. Several existing works proposed different food recommendation systems. These systems are grouped into further categories, namely: (a) Food recommendation model as presented in [12], (b) Menu recommendation approach as implemented in [13], (c) Diet recommendation frameworks as demonstrated in [14] and [15], (d) Health-aware recommendation models as evaluated in [16] and [19], and (e) Physical Activity recommendation framework as designed in [43].

The above-mentioned frameworks provide the recommendations either for generalized health improvement or for diet-related diseases. Most of the recommender systems ignore factors like the user's nutritional needs and the level of disease. For instance, one food recommendation framework generated generic recommendations for diabetes patients [17]. The system needs to additionally consider each patient's glucose level as it may vary from person to person. Similarly, the model should integrate the nutritional factors and values of food to suggest a balanced diet [18]. The system filtered the generated food recommendations based on the user's lifestyle [19]. A study conducted a survey to collect users' information like lifestyle, food preferences, nutrient intake, and habits. The system modelled this information to recommend different meals for daily and weekly basis [20].

Deep learning-based recommender systems are a new trend in the recommendations domain. Some of the studies are analyzed in this work. The system developed the RBM model for generating collaborative filtering-based recommendations [21]. The system assigned a single RBM for every user and considered rated items only. It computed the weights using rated items. The work used the Netflix data for evaluation purposes and the system gained more precise results compared with Netflix's own model. This approach focused on prediction accuracy [21]. The model presented a hybrid method

using user and item-based RBM methods [22]. In this case, both user and item are hidden layer units. The system implemented RBM-CF hybrid model and integrated item features using conditional RBM [23]. The following recommender systems have been reviewed to identify the scope of nutrition and health improvement.

Norouzi et al. [24] developed a snack recommender system for Iranian diabetic patients. A mobile application was developed which used the rule-based system. The system recorded features like patient's profile, physical activity, user's favorites, and periodic reports. Nutritionists validated the system-generated snack items. The experimental results found that the recommended snacks were suitable for Iranian culture. However, the study should suggest other meals as well, like breakfast, lunch, and dinner. Quality of suggested food items may improve using more precise algorithms. The current research work recommends complete meal plans for a day including breakfast, lunch, snack, and dinner.

A hybrid recommender using deep learning-based Long Short-Term Memory method was designed by Chen et al. [25]. The system used genetic algorithms for recommendation of groceries. The work can be improved by using generalized word embedding for grocery related articles. The system should consider stating the correlation between ingredients and nutrients of food items. The current proposed framework recommends suggesting diet plans as per the nutritional requirement of the users.

A rule-based diet recommender system for chronic disease patients was constructed by Chen et al. [26]. The system used a decision tree, ontology, and Jena inference engine. Food ontology created the semantic structure for food and nutrients. Decision tree generated the rules to analyze an individual's personal data and nutritional requirements, and the Jena inference system was used to infer the food items. The system filtered the unsuitable food items for users. The recommendation process should incorporate a personalized approach in terms of users' nutritional needs. The current proposed work provides this personalized approach to recommend diet plans as per users' needs.

Rehman et al. [27] implemented a cloud-based diet recommender system. The model recommended a food list using an ant colony optimization method. The proposed rule-based method updated the heuristic data to maximize the diversity between food items.

The system should recommend all meals in a day. The system should primarily include users' personal food preferences. The current research work focuses on recommendations for all meal types in a day. It takes into consideration a user's food preferences in the recommendation process.

A personalized nutrient-based hybrid meal recommendation system, named Yum-me was developed by Yang et al. [28]. The system was designed to meet dietary restrictions, individuals' nutritional expectations, and food preferences. A questionnaire-based user interface was designed to capture the user profile. The approach, however, lacks in ranking the food items appropriately. The current research work suggests the Top-3 ranked food items model, including user preferences and health conditions.

Bianchini et al. [29] implemented a personalized healthy food recommender framework, named PREFer. This model used medical prescriptions for recommendation purposes. The system used a ranking algorithm to incorporate both the users' preferences and their medical prescriptions. The proposed system needs to also consider user's lifestyles and nutritional habits. The current proposed framework considers the nutritional needs of thyroid patients. Further, it recommends the diet and exercise plans suitable for their lifestyles.

A hybrid recommender model for diabetic patients was developed by Kumar et al. [30]. The food ontology was constructed by combining self-organizing maps and K-Means methods. The diet recommendations were based on user profiles. The system should additionally consider users' nutritional needs, glucose levels and food preferences. The current research work incorporates food preferences and specific health conditions to obtain better and holistic recommendation quality.

Espín et al. [31] developed a healthy diet recommendation model for elderly people. Nutritional assessments were conducted to motivate and engage the users. Food recommendations were generated using semantic similarity measures. The system should use other automated inference methods to enhance its performance. The recommender model should also consider user preferences and eating habits. The current proposed framework uses an improved, deep learning method. It incorporates users' personal and medical profiles and suggests diet plans based on their health-related and preference-based food-items.

A context-based model, named u-BabSang had been proposed by Oh et al. [32]. The system recommends proper foods using an individual's profile, and physiological sensor-based signals. The model also analyses context features like physiological status, weather, and location. It checks a user's medical history to generate recommendations. The model could generate precise recommendations using an increased amount of sensors to capture relevant context information. The system should include a user's food preferences and nutritional needs. The current research work does incorporate the user's health issues and food preferences to provide precise recommendations.

Authors proposed a disease-driven nutrition-based recommendation system. A multi-agent rule-based framework was designed by Ivaşcu et al. [33]. The system retrieved the user's medical profile. It recommended the recipes preferred by the individuals. However, the system needs to further consider the right quantity of ingredients for the selected recipes. Moreover, the system should recommend disease-based nutritional requirements, and include recipes accordingly. The current research work recommends the diet plans considering the individual's calorie intake and health condition. As recommended above, the proposed work incorporates nutritional food items based on thyroid disease related diet.

Terzimehic et al. [34] designed a knowledge-based recommendation framework. It improved its recommendations by tracking the user's food intake. The system recommended a food list using the user's profile and nutritional needs. For further improvement, the system should also include health parameters and food preferences. The current proposed work analyses the health factors and nutritional needs.

Authors designed a context-aware hybrid recommendation system [35]. The system monitored the user's food habits. It provided precautionary ways to reduce the risk of chronic diseases. The model analyzed and monitored the physical activities of the user. The system generated alarms, in order to motivate users to adopt active and healthy lifestyles. The study needs to consider health related food items to enhance the recommendation process. The current research model estimates the health, preference, and similarity scores. It generates precise predictions for diet and exercise plans for users.

A model-based personalized recommendation framework was analyzed by Xie et al. [36]. A study was performed with two experimental groups, Skilled and Starter. The system provided recommendations for minimizing clinical risk for diabetic patients. The hypoglycemia events were observed before and after exercise performed by groups. For better results, the study should include factors like users' fitness level, lifestyle, and psychological aspects. The current research work has integrated all the above factors in its recommendation process.

Zenun et al. [37] proposed a knowledge-based recommender model. The study incorporated features like experts' knowledge, dietary intake, other user's responses, user's preferences, and population data. The system conducted surveys with dieticians. The online RCT- Randomized Control Trial was used to generate ratings for food items. The work could be enhanced using advanced recommender algorithms. Nutritional needs and calorie intake, too, need to be integrated for a more personalized approach. The study should include a feedback mechanism. The current research work adopts feedback from users to revise the recommendations. The feature of user feedback helps improve the usability and quality of the recommender system.

A hybrid food recommender system was presented by Bundasak et al. [38]. The system combined clustering and Weighted Slope One methods. The system recommended food items based on the patient's health condition using the clustering method. The system constructed two clusters to find the characteristics of food and disease. The system should also include the restricted food list for diabetic patients. User groups and food screening need to be improved using precise methods. The current research work analyses the user's profile, health condition and nutritional needs. Moreover, the work recommends the food-items with suitable recommendation algorithms.

Agapitos et al. [39] designed a content-based DIET Operating System (DIETOS). The system could be used by diet-based chronic disease patients and healthy people. The system built the user's health profile. It generated personalized healthy food items using their geographical origin. However, DIETOS can improve its recommendations by using the user's current health condition. The current proposed work uses the hybrid approach. It incorporates the user's personal and current medical profile. The work obtains better results in ratings predictions and recommendation process.

Authors constructed a collaborative filtering food recommender model [40]. The system provided personalized recipe recommendations. These suggestions were produced by using the user's preference dataset. The food preferences were given in terms of ratings and tags. The model used the matrix factorization method. It obtained better accuracy by using tags when compared to ratings. The system found that the predicted recipes matched with the user's actual preferred recipes. Suggestively, the study should consider calorie intake and nutritional factors as well. The prediction model should use negative tags to recommend a balanced food intake. The current proposed diet recommender system generates Top-3 diet and exercise plans taking into consideration calorie intake and health requirements.

Authors designed a smart plate using sensors to detect the food items [41]. The system retrieved information about the type and quantity of food a child ate. It then determined the nutrition intake quantity for the child. The child's growth rate was predicted based on nutrients consumed in a month. A smart plate was given to 10 children for experimental purposes. The menus were divided, using the K-Means method, into four clusters. The recommended menus were created after studying the ingredients consumed by a child in a month. The response was collected from parents and children for the recommended menu through a survey. The system gained a large number of positive responses for recommended food items. The recommender system could be improved using factors like child's food preferences, lifestyle, and psychology status. A smart plate might add an extra financial burden to users in the recommendation process. The current proposed system considers users' health-based food items and adopts a personalized approach.

Allian et al. [42] integrated American-Indians' ontological profile using clinical diabetes guidelines. The system could make personalized diet and exercise recommendations using geographical, socioeconomic, and cultural status of American-Indian patients. The system uses American-Indians' biocultural ontology to achieve a personalization approach. Rule-based logic was derived from the general clinical diabetes guidelines and recommendations. The rules were incorporated with the ontology to create a knowledgebase for the recommender engine. Evaluations were performed with user case studies and validated by medical experts. The sample population was very less to measure the effectiveness of this system. A feedback loop should be considered to increase the usability and quality of this recommender system.

The current proposed model focuses on recommending disease-driven diet plans and it provides a feedback loop to register user responses.

A hybrid recommendation model for runners was proposed by Donciu et al. [43]. The system provided workout and diet plans suitable for users. The semantic ontology-based hybrid model is developed using personal profiles and preferences. The system developed a small-scale mobile application to provide healthy diets for runners. The model should also take into consideration the users' individual health issues. The system needs to consider the usability issue of the recommender system by adding a feedback system. The current research recommends health-related diet and exercise plans. It adopts a feedback loop to increase the usability of the recommender system.

Author implemented an expert system for recommending nutritional food items [44]. The system measured the quantity of each ingredient needed for a normal person and a specific diet-related patient. The system designed an android application, called Slim Line. In its initial state, it had 100 pairs of random values. The system, then, selected a pair of random values having minimum error rate. The optimum neighbor method generated the recommendation solution. Slimline computed the quantity of food ingredients and macronutrients in the range of ±25% of values specified by experts. Additionally, food preference and calorie intake should be included. The database should have more food items with similar ingredients and in the same quantity. The current proposed model generates the diet plans keeping in mind calorie intake and nutritional needs.

Li et al. [45] developed a hybrid model for recommending nutritionally balanced food combos to users. The application was designed for online meal ordering purposes. This model examined the user's demands and used them to design food combo recommendations. A framework managed the challenges that clients faced while picking up a suitable diet plan for themselves. The model combined content and collaborative methods. The content-based algorithm calculated similarity by dividing domains of users and nutritional combos. It computed these similarity values to rate the recommended items. A popularity score was calculated for combos using collaborative methods. The hybrid model recommended similar combos to end-users using joint score of similarity and popularity measures. Factors like calorie intake and food preferences may provide more precise and suitable recommendations. Dataset for

nutritional combo should take care of combined calorie intake. The current proposed recommender model extracts the data from various nutritional blogs and recommends diet plans to meet the user's calorie requirements.

The above-mentioned approaches have their own advantages and drawbacks. Machine learning and collaborative filtering algorithms suffer from data scarcity (cold start) problem. Pre-defined rules are not always available in the context of specific health issues, which is a major drawback when it comes to rule-based approaches. Tremendous research work is carried out in the food and exercise recommendation domain. While most of the recommender systems focus on diabetes, it is also crucial to recognize that Thyroid is a common and the most prominent disease found among women. It affects the body in many ways, including the metabolism. A suitable diet and exercise therapy may provide significant health improvement for thyroid patients. So, there is a need for diet and exercise recommender systems that help thyroid patients to maintain a healthy lifestyle. However, unfortunately, this area is under-researched.

2.1 Challenges

The core challenge faced while conducting this research is to design a personalized recommendation system. The model provides diet and exercise plans for thyroid patients by integrating their food and activities preferences. Further, the framework considers the level of disease as well, which proves to be effective in maintaining thyroid hormone levels. Various previous studies have worked on different health-related issues. These systems recommended general dietary guidelines. However, health-related recommendations should be personalized. Every person has their own preferences and health issues. Therefore, the framework should consider personal data such as disease level, preferences, calorie intake and nutritional needs for a more personalized approach. To meet these requirements, efficient recommendation methods, like the deep learning method, need to be identified.

3. PROBLEM STATEMENT AND OBJECTIVES

3.1 Problem Statement

A personalized diet and exercise recommendation framework is designed for thyroid patients. The system constructs diet and exercise plans based on the patient's nutritional needs. The proposed system extracted data from thyroid patient’s personal and medical profiles. It also incorporates food and activity preferences, along with calorie intake suggestions. The system computes a health score for each patient and the targeted patients are identified using their health score. The preference score is generated using a food-item rating matrix. The proposed deep learning hybrid model is used to recommend the suitable diet and exercise plan. It uses health, similarity, and preference scores to generate accurate recommendations. A feedback mechanism is also included to record the user’s response to recommended items.

3.2 Objectives

3.2.1 Primary Objective

To design a personalized diet and exercise recommendation framework based on food preferences for thyroid patients.

3.2.2 Secondary Objectives

1. To capture and analyze the publicly available datasets: a) Food-items with their nutritional values, b) User's personal and medical profiles, c) Physical exercises with duration, and d) Food ratings.

2. To compute and integrate the patient’s nutritional needs and calorie intake using content-based features.

3. To develop a hybrid deep learning personalized model using three system-generated scores: a) Health score (content-based), b) Similarity score (collaborative filtering-KNN), and c) Preference score (content-based KNN).

4. METHODOLOGY

4.1 Proposed Model Description

The proposed recommender model aims to recommend Top-3 diet and physical activities plans. For this purpose, the model integrates the user's thyroid condition and preferences. The proposed diet and exercise recommendation framework serves as a personalized solution for thyroid patients. The model computes the average summation of the user's health condition and preferences. Suppose, N_u users and N_f foods are there in a training dataset. The dataset contains three columns: user_id, food_id, and ratings. Let $X_{u,f}$ be a "user-food matrix" which does not contain missing values for food ratings. The matrix $Y_{u,f}$ is a rating matrix for each user.

$$X_{u,f} = \begin{bmatrix} id_u & id_f & r_{u,f} \\ . & . & . \\ . & . & . \end{bmatrix} \text{ and } Y_{u,f} = \begin{bmatrix} r_{u1,f1} & \dots. & r_{u1,fi} \\ . & \dots. & . \\ . & \dots. & . \\ r_{ui,f1} & \dots. & r_{ui,fi} \end{bmatrix}$$

The proposed system first predicts the ratings of all users for the available food-items in the training dataset. Each rating falls between the range of 1 and 5. The aim is to reduce the RMSE error (Root-Mean-Square-Error) for the testing dataset, which contains unknown ratings for the food-items. The testing dataset and estimated error are defined as below:

$$D_{Test} = ([id_u \quad id_f], \dots), \text{ where } id_u, id_f \in X_{u,f} \text{ and } r_{u,f} \notin X_{u,f}$$

$$E_{u,f} = r_{u,f} - p_{u,f} \qquad (1)$$

where, $r_{u,f}$ is actual available rating in a testing dataset and $p_{u,f}$ is a predicted rating estimated by the proposed system.

In the next process of recommendation, the proposed model generates a health score. This score lies between 1-10 and is computed by comparing the user's health profile, calories intake, and nutritional needs. The recommendation model sorts the predicted diet and exercise plans using health scores. The model calculates the similarity and preference scores to suggest Top-3 recommendations for diet and exercise. The predicted score, health score, and the Top-3 recommended diet and exercise food plans are defined as below:

$$P\_List_{u,p_f} = \begin{bmatrix} id_u & p_{u,f} \\ . & . \\ . & . \end{bmatrix}$$

$$P\_List_{u,p_e} = \begin{bmatrix} id_u & p_{u,e} \\ . & . \\ . & . \end{bmatrix}$$

where, P_List_{u,p_f} and P_List_{u,p_e} are sorted decreasing list of predicted food-items and exercises respectively.

$$H\_Score_{u,f} = \sum_{(u,f)\in \mathrm{P\_List}_{u,p_f}} \frac{h_{fi}}{h_{ui}} \times x_i \qquad (2)$$

where, h_{fi}*:* Nutritional value of the food-items; h_{ui}*:* Required nutritional values of food-item based on thyroid disease type; $x_{i:}$ Weight of a nutritional component of a food-item.

$$R\_List_{u,P\_list_f} = [\ p_{u,f} \times\ x_{u,n} + H\_Score_{u,f} \times\ x_{u,pf}\ , \ldots\ldots] \text{ , (u,f)} \in D_{Test} \qquad (3)$$

$$R\_List_{u,P\_list_e} = [\ R\_List_{u,P\_list_f} \times\ x_{u,pe}, \ldots\ldots] \qquad (4)$$

where, R_List_{u,P_list_f} and R_List_{u,p_list_e} : Recommended Top-3 diet and exercise plans for user u respectively; $x_{u,n}$: Weights as per nutritional needs of users; $x_{u,pf}\ and\ x_{u,pe}$: Weights as per food-item and exercise preferences.

4.2 Model Flow Process

The proposed model is designed and evaluated with three recommendation algorithms. The model uses content-based, collaborative filtering KNN and Conditional RBM.

Fig.1 displays the process flow of the proposed hybrid model. The system integrates the content-based attributes with conditional RBM. The proposed approach works in the following four steps:

1. The system collects the following data from online available sources:
    a. User demographic and thyroid profile
    b. Food with their nutritional values like calories, fats, proteins, carbohydrates, sodium, iodine, zinc etc
    c. Physical exercises with intensity and duration
    d. Food ratings
2. Content-based method integrates the user's demographic, medical profile and preferences. The health score is computed using these content features.
3. The similarity score is computed using collaborative KNN method and the preference score is computed using Content-based KNN method.
4. The proposed model designs the hybrid recommendation system using similarity, preference, and health scores. These scores are given as input to the conditional RBM. The proposed CB-NCRBM model integrates all these scores as inputs to visible units. The model predicts the list of diet and exercise plans. The feedback loop is included in the recommendation process. Top-3 plans are recommended to users based on prediction score. Fig.1 describes the process flow of the proposed model.

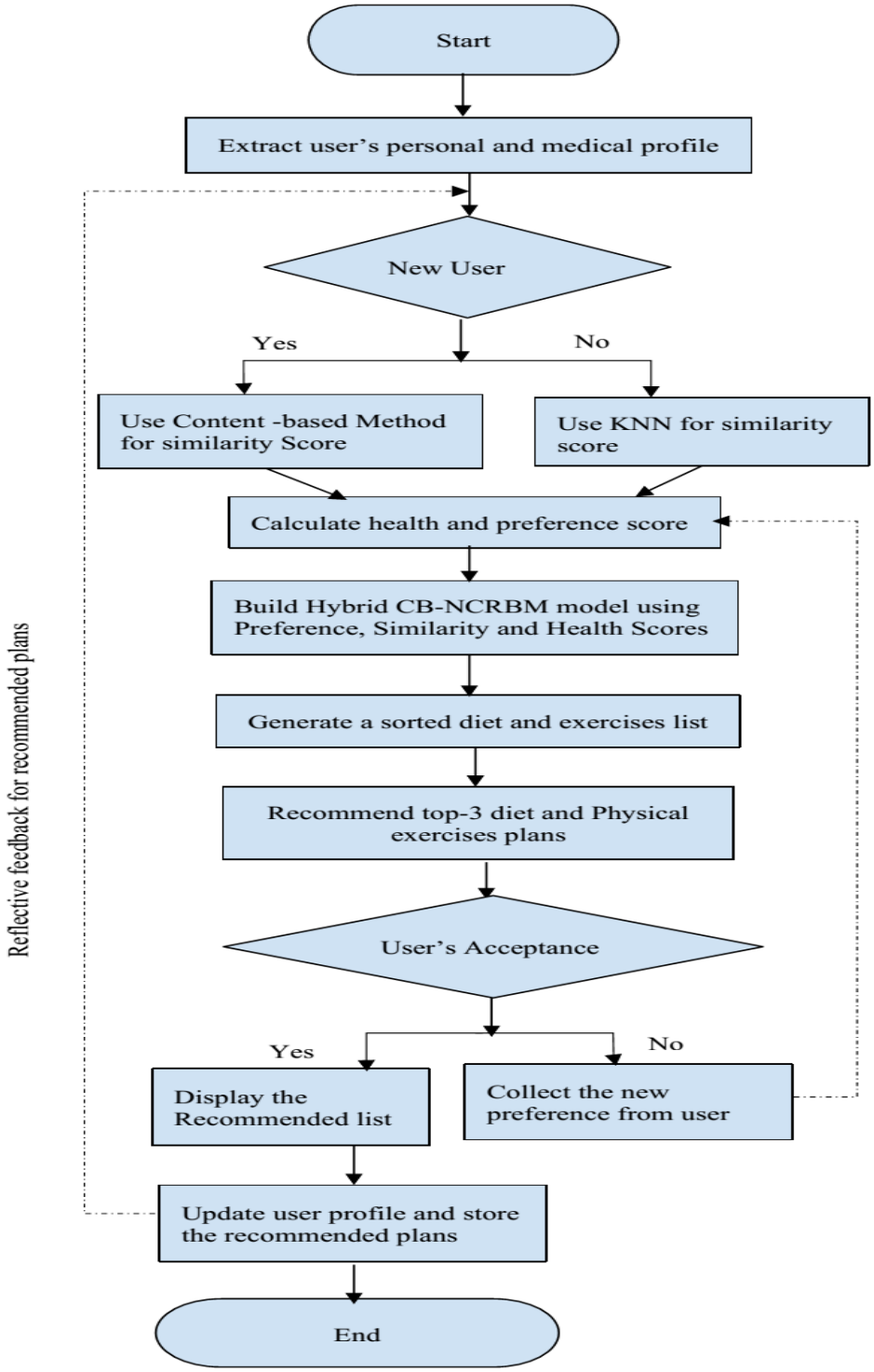
Start
Extract user's personal and medical profile
New User
Yes
No
Use Content -based Method for similarity Score
Use KNN for similarity score
Calculate health and preference score
Build Hybrid CB-NCRBM model using Preference, Similarity and Health Scores
Generate a sorted diet and exercises list
Recommend top-3 diet and Physical exercises plans
User's Acceptance
Yes
No
Display the Recommended list
Collect the new preference from user
Update user profile and store the recommended plans
End
Reflective feedback for recommended plans

Fig.1 Model Process Flowchart

4.3 Methods Used

4.3.1 Content-Based KNN

Content-based approach utilizes discrete properties of an item and it recommends other items with similar characteristics to the user. The food-items need to be extracted using similar user's experiences. So, content-based methods are used to get the similarity among food-items. K-Nearest Neighbour is used to find similarity among users that provided similar ratings on food-items. Content-based KNN predicts preference scores using content features and similarity amongst users. The following steps are involved in building a Content-based KNN method:

1. It first computes a food-item similarity matrix using content features such as disease type food preference, personal profile, and activity preference
2. The method builds up the similarity scores between food-items
3. It extracts the most-similar top-K ratings
4. Finally, the method computes the average similarity score of k-neighbours (k=10) with weighted sum approach

4.3.2 Restricted Boltzmann Machines

RBM was proposed by Ruslan Salakhutdinov in 2007 [21]. It is the first neural networks-based recommender model. RBM is an energy- based and generic stochastic deep learning model which learns the likelihood of distribution over the input dataset [46]. RBM has two layers with a visible layer as input and another hidden layer. RBM restricts the intra-layer interaction between the neurons and the visible input layer is restricted to use binary values. Therefore, one-hot vector of rating score is encoded for the adaption of this restriction. The performance of RBM may improve by adding more visible or hidden units. Contrastive divergence is an approximation algorithm used in RBM to employ gradient descent [5]. Fig 2 shows that RBM uses Bernoulli values for visible (V) as well as hidden (H) layers. The weight matrix W stands for connectivity strength among visible units V_i and hidden units H_i. The RBM model adds biases and weights to these units.

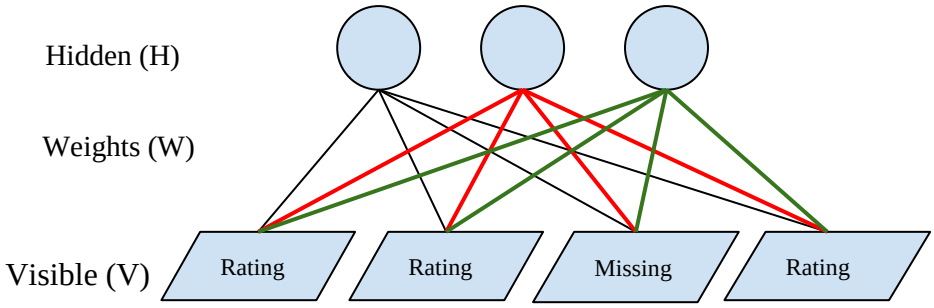

Fig. 2. RBM Model

4.3.3 Hybrid CB-NCRBM Model

The proposed CB-NCRBM model integrates similarity, preference and health scores. Three extra visible layers similarity (S), preference (P) and health (H_Score) are additionally introduced to pure RBM. In this model, hidden layer H is fully connected with visible layers V, S, P, and H_Score as given in Fig 3. However, visible layers do not interact with each other.

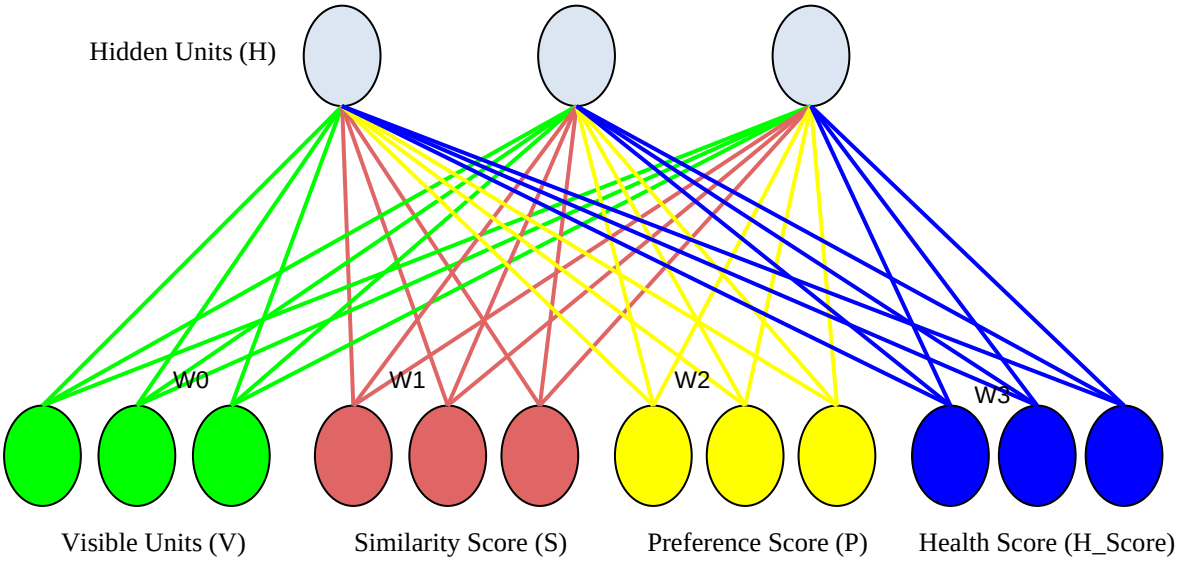

Fig.3 Proposed Hybrid Model

There is a unique RBM for each user with shared parameters. For example, a user *u* has rated *f* food-items, then there are *f* visible units.

4.4 Proposed Model Formulation

The collaborative filtering method faces the cold-start issue when a new user comes into the system [47]. The proposed CB-NCRBM model includes the similarity, preference, and health scores to overpower such an issue. The hybrid model uses the content features of new users to generate similarity scores.

Similarity score for a user is the probability distribution of neighbor's ratings for a particular food item. The cosine similarity is estimated among user *u* and its neighbours [48]. Cosine similarity considers positive ratings which is calculated with the angle generated by two rating vectors. The model finds the neighbours with similar thyroid disorder. The similarity score of food-item *f* for user *u* is estimated as in (5):

$$S(u,f) = \frac{\sum_{x \in Ku} R(x,f)}{K(u)} \tag{5}$$

where, *Ku*: Set of similar thyroid disorder neighbours; *K(u)*: Number of neighbours of user *u*; and *R(x,f)*: Food preferences f (0/1) given by neighbor *x*.

The preference score is calculated as the distribution of user's ratings given for food-item *f*. The food-item with the highest preference is selected amongst the similar users. The preference score of food-item *f* in a dataset *S* is given as in (6):

$$P(s,f) = \frac{\sum_{i \in Su} R(i,f)}{S(u) R_{max}} \tag{6}$$

where *Su*: Set of data instances of dataset; *S(u)*: The complete dataset; *R(i,f)* : The rating of food-item *f* in data instance *i*; R_{max} : Maximum rating of food-item *f* in *Su*.

The hybrid model used the conditional Bernoulli distribution to each column of visible unit V_i and hidden unit H_j. If the user rated the food-item then V_i =1 and if not, V_i = 0. The similarity score S_i is provided by layer S. This layer has user *u's* neighbours and their rating for food-items *fi* (i=1...n). The layer P provides the preference score P_i for food-item *f* preferred by the user u_i (i=1…k). The layer H_Score presents the comparison among user's nutritional needs with the available food nutritional values. The connection among the hidden H_j and the visible units S_i, P_i and H_Score_i are presented using weight matrices *W1*, *W2*, and *W3* respectively. The joint distribution scores for proposed model is defined in (7). A conditional distribution score for visible

units is described in (8). Similarly, conditional distribution scores of similarity S_i, preference P_i and health H_Score_i are defined in (9), (10) and (11) as below:

$$P\left(H_j = 1 \middle| V, S, P, H_S core\right) =$$

$$\sigma\left(b0_j + \sum_{i \in V} V_i \, W0_{ij} + \sum_{i \in S} S_i \, W1_{ij} + \sum_{i \in P} P_i \, W2_{ij} + \sum_{i \in P} H\_Score_i \, W3_{ij}\right) \quad (7)$$

$$P(V_i = 1|H) = \sigma\left(b0_i + \sum_{i \in V} H_j \, W0_{ij}\right) \quad (8)$$

$$P(S_i = 1|H) = \sigma\left(b1_i + \sum_{i \in S} H_j \, W1_{ij}\right) \quad (9)$$

$$P(P_i = 1|H) = \sigma\left(b2_i + \sum_{i \in P} H_j \, W2_{ij}\right) \quad (10)$$

$$P(H\_Score_i = 1|H) = \sigma\left(b3_i + \sum_{i \in H\_Score} H_j \, W3_{ij}\right) \quad (11)$$

Biases *b0*, *b1*, *b2*, and *b3* are added by CB-NCRBM model to weight matrices, *W0*, *W1*, *W2*, and *W3*. The Sigmoid σ activation function is used in this model. The small random zero-mean gaussian values are initialized to weights using standard deviation [6]. The rating of the new food-item is predicted using (7). The predicted rating for new food-item n is estimated by the proposed model. The conditional distributions for rating prediction are defined in (12) and (13) as below:

$$\hat{P}\left(H_j = 1 \middle| V, S, P, H_S core\right) =$$

$$\sigma\left(b0_j + \sum_{i \in V} V_i \, W0_{ij} + \sum_{i \in S} S_i \, W1_{ij} + \sum_{i \in P} P_i \, W2_{ij} + \sum_{i \in P} H\_Score_i \, W3_{ij}\right) \quad (12)$$

$$P(V_n = 1|\hat{P}) = \sigma\left(b0_n + \sum_{i \in V} \hat{P}_j \, W0_{nj}\right) \quad (13)$$

The proposed model uses contrastive divergence for conditional distribution defined in (7)-(11).

5. EXPERIMENTS AND EVALUATION

5.1 Datasets

Various Indian food-items which are easily available, nutrition and physical exercise information was gathered. The extracted data was analyzed to obtain thyroid related diet and exercise programs. Several thyroid related nutrition blogs and forums were also analyzed. Generic thyroid diet recommendations websites are scrapped to generate user food-item rating matrix. Each rating has either 1(liked) or 0(dislike) value. The user's personal profile was created based on available information such as age, gender, weight (kg), height (cm), food preference, activity preference, and thyroid disease-level. Food data with their nutritional values is obtained from Indian Food Composition Tables (IFCT 2017) published by National Institute of Nutrition, India. The food dataset is generated based on thyroid diet requirements. The food database has features like food-name, food-type, meal-type, calories, fats, proteins, carbohydrates, sodium, zinc, and iodine. The activity dataset has features like exercise type, amount of calories burned, and duration of the workout.

5.2 Evaluation Metrics

The performance of the proposed CB-NCRBM model is evaluated using various metrics. Recommendation error and classification accuracy metrics are evaluated to validate the generated recommendations.

5.2.1 RMSE (Root Mean Squared Error) and MAE (Mean Absolute Error)

RMSE measures the inaccuracies for all available ratings. It is suitable to predict a given recommendation or classification task. However, RMSE is appropriate for few situations where differentiations between errors are not considered [49]. The RMSE calculates the difference among actual and predicted results over the sample dataset. RMSE is defined as:

$$RMSE = \sqrt{\frac{1}{|D_{Test}|}\left(\sum\left(E_{u,f}\right)_{u,f \in D_{Test}}{}^{2}\right)} \quad (14)$$

MAE measures the absolute differences among the predicted ratings with their actual ratings. MAE is defined as:

$$MAE = \frac{1}{D_{Test}} \sum \left| E_{u,f} \right|_{(u,f) \in D_{Test}} \quad (15)$$

where $E_{u,f}$ is described in (1).

5.2.2 Classification Accuracy Metrics

Accuracy metrics prove efficiency in terms of decision-making abilities of recommendation algorithms. These measures compute the number of true and false predictions. The proposed model uses these metrics for finding relevant or irrelevant food-items generated by the recommendation process. Therefore, these metrics sometimes may ignore the exact ranking or rating of food-items. Accuracy metrics considers only true or false classification and these metrics convince users to make certain decisions either to select or reject a food-item. Confusion matrix provides the description of the model's performance over testing the dataset for known true values. Table I describes the confusion matrix as follows:

Table I: Confusion Matrix

Actual Class Values	Predicted Class Values	
	Recommended	Not recommended
Preferred	True-Positive Value (TPV)	False-Negative Value (FNV)
Not preferred	False-Positive Value (FPV)	True-Negative Value (TNV)

Accuracy estimates the true prediction with respective of entire dataset. It is formulated as follows:

$$Accuracy = \frac{TPV+TNV}{TPV+TNV+FPV+FNV} \quad (16)$$

A recommender framework usually suggests a recommended list of items to users. Users are generally accepting the recommendations which match their choices. This kind of generation of recommendations is considered as Top-n recommendations. The proposed system uses Precision, Recall (sensitivity) and F-Measure to evaluate the recommendation framework’s performance. Precision and Recall are defined as follows:

$$Precision\ (p) = \frac{TPV}{TPV+FPV} = \frac{R_{rp}}{R_t} \quad (17)$$

$$Recall\ (r) = \frac{TPV}{TPV+FNV} = \frac{R_{r.p}}{R_{u.p}} \quad (18)$$

where, R_{rp}: Recommended food-items preferred by a user; R_t: Total recommended food-items; and $R_{u.p}$: Total number of food-items preferred by user.

Precision of the recommender system depicts the proportion of food-items preferred by the user. Recall denotes the number of favorite food-items recommended by the system. The recommendation systems generally give more attention to generate top-n precise recommendations. F-Measure is a trade-off among Precision and Recall scores. It interprets the weighted average of Precision and Recall scores. F-Measure with value 1 is treated as best while value 0 is considered as worst. In the recommendation process, F-measure provides the overall utility for the generated recommended item list. F-Measure is computed for each user. Average of all F-Measure scores provides top-n recommendations. F-Measure is given as below:

$$F - Measure = 2\ \frac{p\ *\ r}{p + r} \quad (19)$$

where, *p* and *r* are described in (17) and (18).

5. 3 Tools Used

The experiments are performed using following tools:

- **Python-3.6:** Python is an interpreted language used for implementing machine learning methods by using Scikit-Learn and other libraries.
- **Surprise:** It is a Simple Python Recommender System Engine which has Python Scikit library to build, analyse and evaluate the recommendation systems.
- **TensorFlow-1.10.0:** TensorFlow framework is developed for modelling machine learning applications. It mainly used to build and deploy neural network methods and deep learning methods.

5.4 Experimental Setup and Results

Content-based KNN method uses the content features such as the user's personal and health profile. The feature vector is generated for every user-food-item pair. The actual rating of each data instance is considered as a classification label. KNN determined the nearest *k* users using Euclidean distance. Weighted average of *k* values is calculated for the estimation of missing ratings. The RBM model updates the biases and weights in a stochastic way. RBM model used learning rate is 0.10/training dataset, momentum is 0.8 and weight decay is 0.001. To reduce the training time, the model used T=0 for contrastive divergence. Content-based KNN, RBM and hybrid model (CB-NCRBM) are implemented using python 3.4. The hybrid model is compared with content-based and other collaborative filtering methods as given in Fig.4.

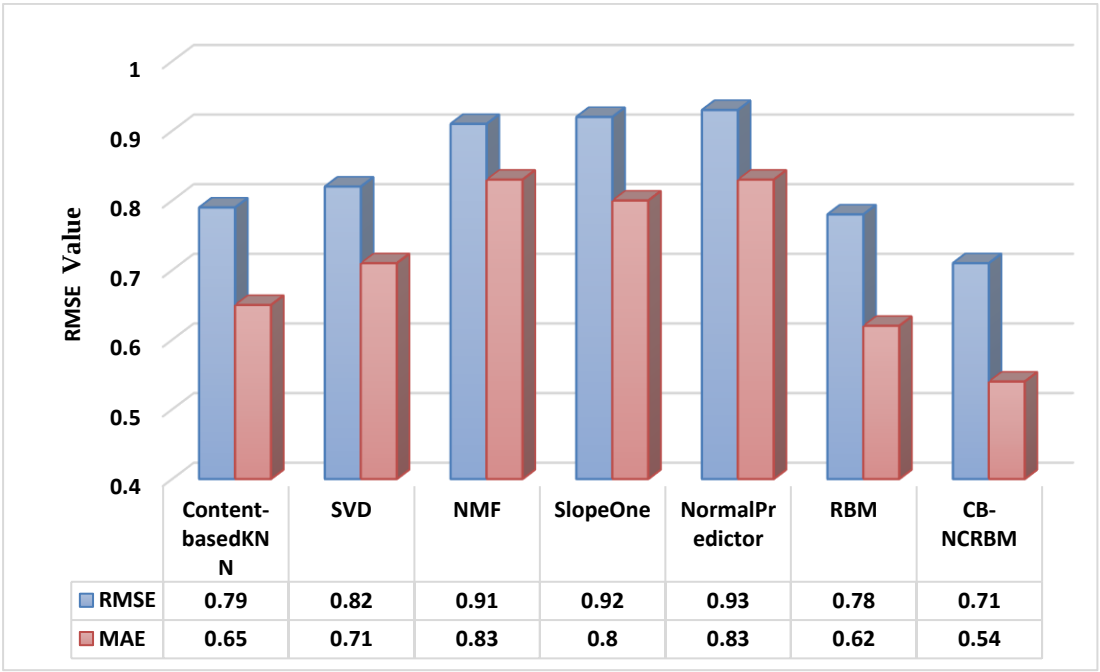

Fig. 4. Comparison between Different Recommendation Methods and Hybrid Model

The comparison between Content-based KNN, Other collaborative filtering approaches, pure RBM and proposed CB-NCRBM is displayed in Fig.4. The hybrid CB-NCRBM significantly outperforms the other models. The learning capacity of RBM models is affected by total units in the hidden layer. These hidden layer units use automatically learned features. The CB-NCRBM model is learned using a different number of hidden units. The

activation function, sigmoid is applied for training and testing of the model. Fig.5 displays the variation in RMSE values for different hidden units.

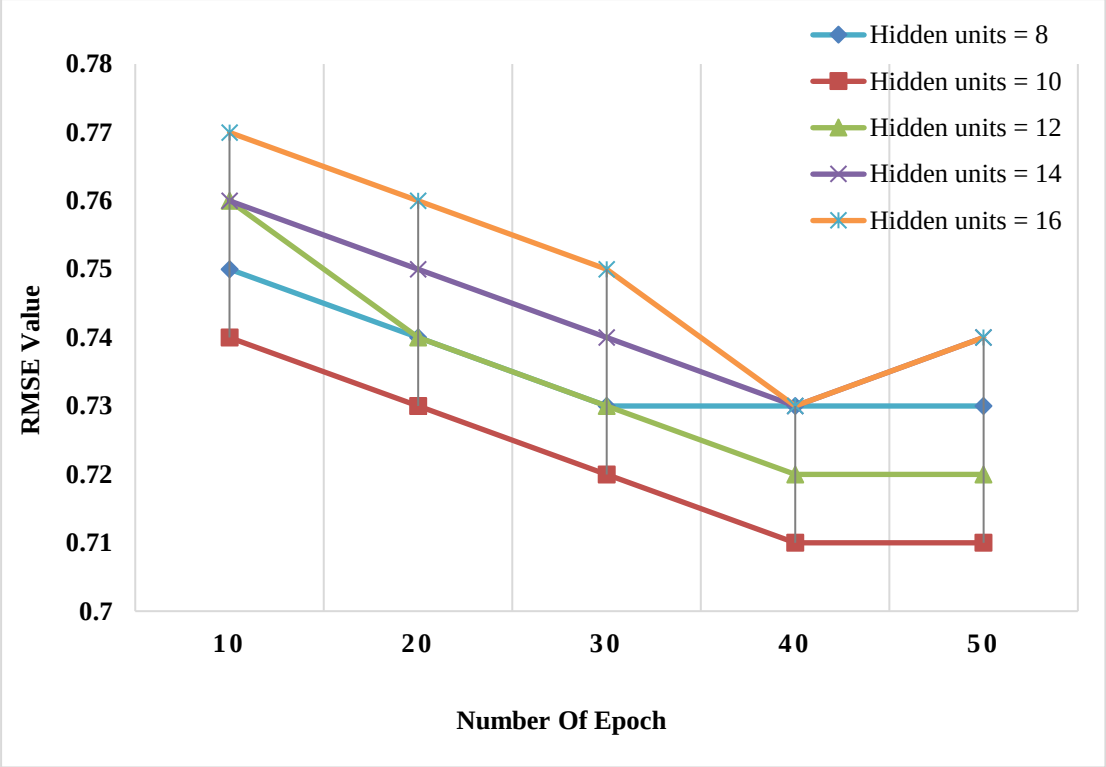

Fig.5 CB-NCRBM Model's Performance with Different Hidden Layer Units

The selection of hidden units may affect the RBM's learning ability. These units represent the learned parameters. The model evaluated with 8,10,12,14 and 16 hidden layer units. The hybrid model achieves the optimal result with 10 hidden units. As hidden units increase, the error rate also increases. The model gives better results for 10 hidden layers and with 40-50 epochs. The RMSE value decreases with the increase in number of epochs. Experiments demonstrate that the larger RMSE values are generated with increase in hidden layer units.

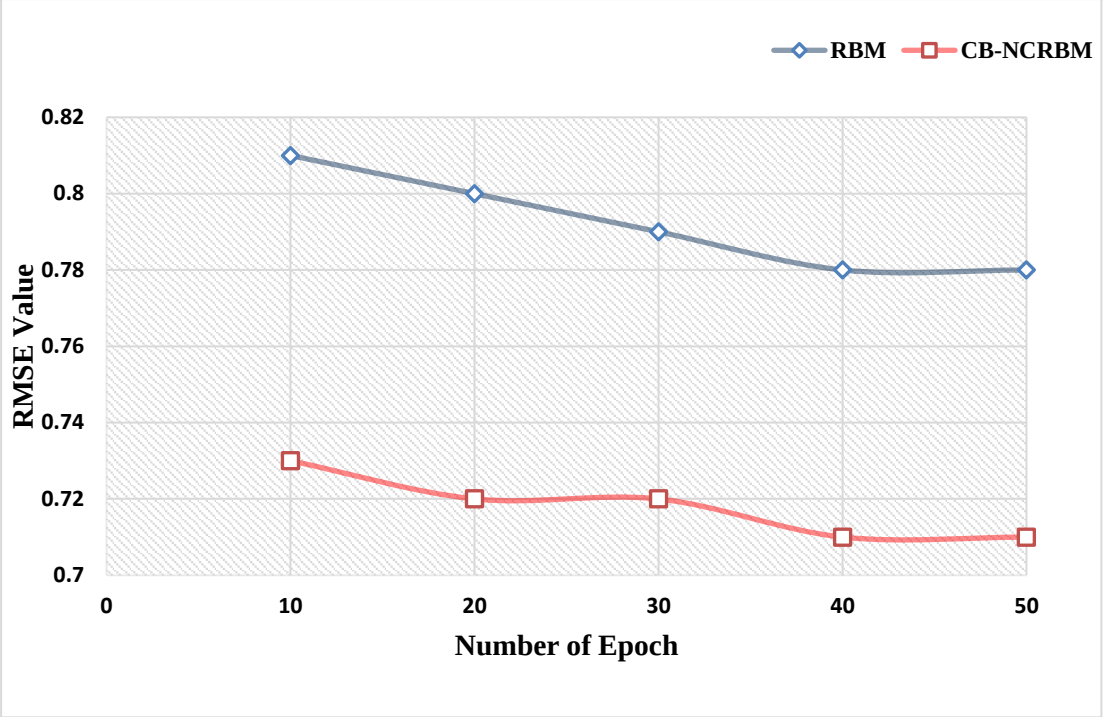

Fig. 6. Performance of RBM and CB-NCRBM with Different Subsets of Sample Data

A pure RBM and hybrid model are compared in Fig.6. The CB-NCRBM model provides the better output than pure RBM as the layers S, P and H_Score have been incorporated with the content-based features of the food-items. These features are applied to visible layer units using estimated scores of similarity, preference, and health. The CB-NCRBM model achieves better performance for number of epochs between 40-50. Accuracy and F-Measure scores for the three evaluated models are displayed in Fig.7.

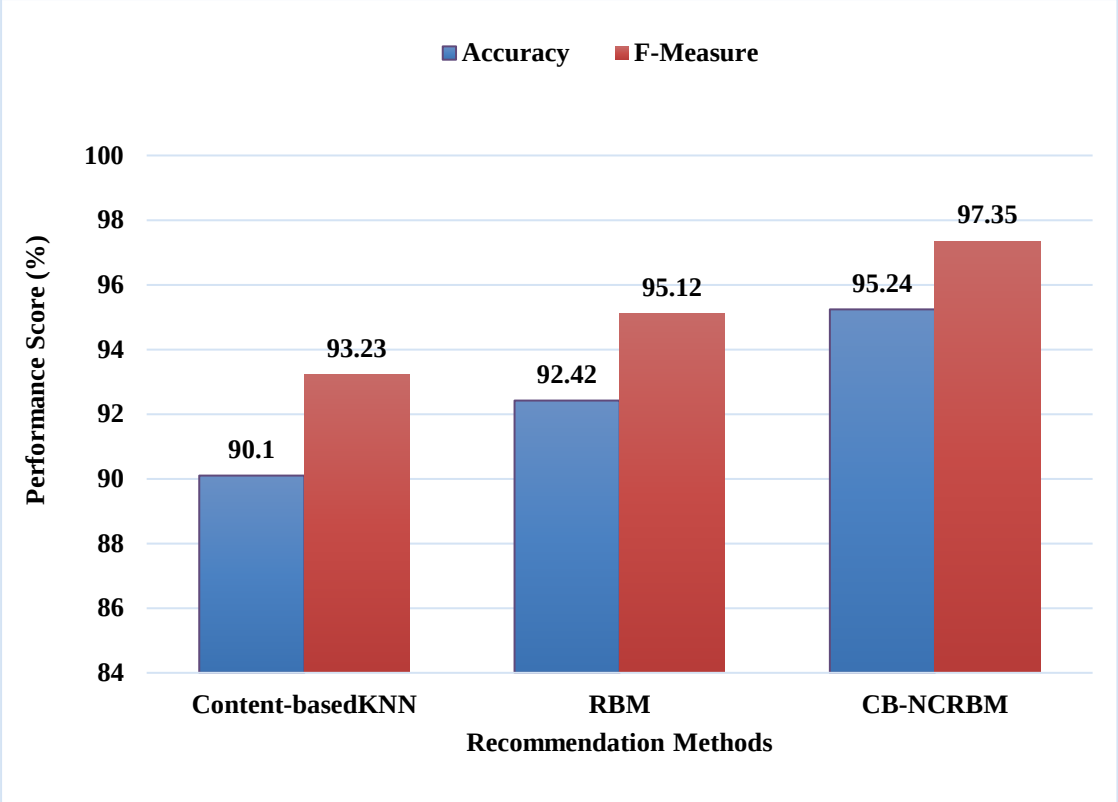

Fig.7. Performance of Hybrid and other Recommendation Models

The CB-NCRBM model achieves the highest accuracy rate as displayed in Fig 7. The improved hybrid model gains 95.24% accuracy rate. Whereas, Content-based KNN and pure RBM model achieve 90.10% and 92.42% respectively. The proposed CB-NCRBM achieves a higher F-Measure score of 97.35% than other recommender methods. The proposed model finds better results than other content-based and collaborative filtering methods.

6. CONCLUSION AND FUTURE WORK

A prediction-based recommender system is currently gaining popularity in the food recommendation domain. Predicting the right food-item and exercises for thyroid patients is challenging and this research work proposes a hybrid CB-NCRBM model to estimate joint distribution of similarity, preference, and health scores. These scores predict the list of food-items and activities based on the user's health condition and preferences. The model then recommends the Top-3 diet and exercise plans to a user. The proposed model uses blogs and online available recipes data to build the sample dataset. The optimal model features are identified by using different combinations of sub datasets of sample data. The proposed CB-NCRBM outperforms compared with other recommendation methods. The hybrid model gains higher accuracy and lesser recommendation error scores. This model could be extended to incorporate context-based features like location, climate, and seasonal availability of food-items. Another extension for this proposed work is to include food images dataset to enhance user experience, along with other promising recommender algorithms.

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LIST OF PUBLICATIONS

I. Conferences:

1. Presented a paper titled, “Recommendation Framework for Diet and Exercise based on Clinical Data: A Systematic Review”, in ACM Women in Research, International Symposia on Data Science and Big Data Analytics ACM-WIR 2018 at Sri Aurobindo Institute of Technology, Indore, India on 5th-6th January 2018.
   https://link.springer.com/chapter/10.1007%2F978-981-10-7641-1_29

2. Presented a paper titled, “Classification of Hypothyroid Disorder using Optimized SVM Method”, in Scopus Indexed IEEE 2nd International Conference on Smart Systems and Inventive Technology (ICSSIT 2019) at Francis Xavier Engineering College, Tirunelveli, India on 27th -29th November 2019.
   https://ieeexplore.ieee.org/document/8987767

3. Presented a paper titled, "Recommendation of Diet using Hybrid Collaborative Filtering Learning Methods", in Springer (Scopus Indexed) - International Conference on Advances in Computational Intelligence and Informatics (ICACII- 2019) at Anurag Group of Institute, Hyderabad, India on 20th -21st December 2019.
   https://www.springer.com/gp/book/9789811533372

4. Presented a paper titled,” Recommendations of Food-items to Thyroid Patients using Content Features”, in Springer (Scopus Indexed) International Conference on Data Science for Computational Security (IDSCS 2020) at CHRIST (Deemed to be University), Lavasa, Pune, India on 13th -14th March 2020.

II. Journals:

1. Paper titled “Physical Fitness Recommender Framework for Thyroid Patients using Restricted Boltzmann Machines” has been accepted for publication with International Journal of Intelligent Engineering and Systems, Publisher: Intelligent Networks and Systems Society, ISSN:2185-310X, E-ISSN:2185-3118. http://www.inass.org/publications.html/
   Scopus Link: https://www.scopus.com/sourceid/21100199790

2. Submitted paper titled, “Evaluation of Ensemble Methods for Multi-label Classification of Hypothyroid Disease”, Expert Systems with Applications, Publisher: Elsevier, ISSN:0957-4174.
   Scopus Link: https://www.scopus.com/sourceid/24201
   Manuscript Number: ESWA-D-20-00316
   Status: Required reviews completed (The paper is with editor for his final decision)

3. Submitted paper titled "Diet and Workout Recommendation System using Improved Restricted Boltzmann Machines", International Journal of Computing, Publisher: Research Institute of Intelligent Computer Systems, ISSN:1727-6209, E-ISSN:2312-5381.
   Scopus Link: https://www.scopus.com/sourceid/21100820054
   Manuscript Number: IJC-1684
   Status: The paper is under review process

III. Book Chapter:

1. Vairale V.S., Shukla S., "Recommendation Framework for Diet and Exercise based on Clinical Data: A Systematic Review", In: Data Science and Big Data Analytics, Lecture Notes on Data Engineering and Communications Technologies, Springer Nature Singapore, Series Volume 16, pp. 333-346 (2019), Print ISBN 978-981-10-7640-4, Online ISBN 978-981-10-7641-1
   DOI: https://doi.org/10.1007/978-981-10-7641-1_29
   Available on: https://www.springer.com/in/book/9789811076404/

2. Vairale V.S., Shukla S.," Recommendation of Diet Using Hybrid Collaborative Filtering Learning Methods", In: Advances in Computational Intelligence and Informatics, ICACII 2019, Lecture Notes in Networks and Systems, vol 119. Springer, Singapore, pp 309-318 (2020), Print ISBN 978-981-15-3337-2, Online ISBN 978-981-15-3338-9,
   DOI: https://doi.org/10.1007/978-981-15-3338-9_36
   Available on: https://link.springer.com/chapter/10.1007/978-981-15-3338-9_36

Recommendation Framework for Diet and Exercise Based on Clinical Data: A Systematic Review

Vaishali S. Vairale and Samiksha Shukla

Abstract Nowadays, diet and exercise recommender frameworks have gaining expanding consideration because of their importance for living healthy lifestyle. Due of the expanded utilization of the web, people obtain the applicable wellbeing data with respect to their medicinal problem and available medications. Since diseases have a strong relationship with food and exercise, it is especially essential for the patients to focus on adopting good food habits and normal exercise routine. Most existing systems on the diet concentrate on proposals that recommend legitimate food items by considering their food choices or medical issues. These frameworks provide functionalities to monitor nutritional requirement and additionally suggest the clients to change their eating conduct in an interactive way. We present a review of diet and physical activity recommendation frameworks for people suffering from specific diseases in this paper. We demonstrate the advancement made towards recommendation frameworks helping clients to find customized, complex medical facilities or make them available some preventive services measures. We recognize few challenges for diet and exercise recommendation frameworks which are required to be addressed in sensitive areas like health care.

Keywords Health care · Food · Nutrition · Diet and exercise recommendation frameworks

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D. K. Mishra et al. (eds.), *Data Science and Big Data Analytics*,
Lecture Notes on Data Engineering and Communications Technologies 16,
https://doi.org/10.1007/978-981-10-7641-1_29

Recommendation of Diet Using Hybrid Collaborative Filtering Learning Methods

Vaishali S. Vairale and Samikshal Shukla

Abstract These days, various recommender systems exist for online advertisement services which recommend the products considering users' interests. Similarly, health recommendation systems are becoming most important component in individual's life. Due to the modernization and busy schedule, people give less concern to their eating patterns. This leads to various health issues like obesity, thyroid disorder, diabetes and others. Every individual has different health issues and food habits. Therefore, diet recommendations should be suggested by considering their personal health profile and food preferences. So, it becomes essential to analyze individuals' health concerns before recommending the diet with required nutrient values. Thus, it helps people to minimize the further risks associated with the current health conditions. The proposed diet and exercise recommender framework suggests a balanced diet for thyroid patients. It takes care of the food intake with necessary nutrients requirement based on thyroid disorders. This paper applies K-nearest neighbor collaborative filtering models using various similarity measures. The paper assessed two-hybrid learning methods, KNN with alternating least squares: KNN-ALS and KNN with stochastic gradient decent: KNN-SGD. The experimental setup analyzed and evaluated the performances of all algorithms using mean absolute error (MAE) and root mean squared error (RMSE) values.

Keywords Collaborative filtering · Recommender system · K-nearest neighbor · Matrix factorization · Thyroid disorder

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R. R. Chillarige et al. (eds.), *Advances in Computational Intelligence and Informatics*, Lecture Notes in Networks and Systems 119,
https://doi.org/10.1007/978-981-15-3338-9_36

acm Chapter Event

Sri Aurobindo Institute of Technology

International Symposium on Data Science and Big Data Analytics

Women in Research

ISDB ACM-WIR 2018

5th-6th January, 2018

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This is to certify that Prof./Dr./Mr./Ms. Vaishali Vairale has presented a paper/ delivered Invited Talk/Chaired Session entitled Recommendation frame work for Diet and Exercise based on clinical data : A Systematic review in the International Symposium on Data Science and Big Data Analytics at Sri Aurobindo Institute of Technology, Indore 5th-6th January, 2018.

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has successfully presented a paper entitled

Classification of Hypothyroid Disorder using Optimized SVM Method

in the 2nd International Conference on Smart Systems and Inventive Technology (ICSSIT 2019) organised by Francis Xavier Engineering College during 27-29 November, 2019 at Tirunelveli, India.

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This is to certify that Prof./Dr./Mr./Ms. Vaishali S Vairale has participated & presented the Paper Id 134 & Titled Recommendation of Diet using Hybrid Collaborative Filtering Learning Methods at International Conference on Advances in Computational Intelligence and Informatics (ICACII- 2019) organized by Department of Computer Science & Engineering, Anurag Group of Institution ,Hyderabad, India on 20th& 21st December 2019.

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has presented a paper titled. Recommendation of Food-items to Thyroid Patientsusing Content-based KNN Method
in the International Conference on DATA SCIENCE AND COMPUTATIONAL SECURITY (IDSCS 2020) organized by Dept. of Computer Science, CHRIST (Deemed to be University), Pune Lavasa Campus, in association with Springer & Computer Society of India, on 13-14 March, 2020.

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Intelligent Networks and Systems Society

Acceptance Letter

International Journal of Intelligent Engineering and Systems (IJIES)

June 29, 2020

Dear Vaishali S Vairale,

Manuscript Title: Physical Fitness Recommender Framework for Thyroid Patients using Restricted Boltzmann Machines

Author(s): Vaishali S Vairale, Samiksha Shukla

Thank you for submitting your paper to the International Journal of Intelligent Engineering and Systems (IJIES). Based on double blind review process, we are pleased to inform you that our Review Committee has accepted your paper.

The paper will be included in the IJIES, which will be published with ISSN (ISSN: 2185-3118) in online on the website (http://www.inass.org/publications.html).
We are looking forward to your further contribution to our journal.

Kind regards

Prof. Dr. Kei EGUCHI
Editor-in-Chief, International Journal of Intelligent Engineering and Systems

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